A Case Study on Student Achievement in Mathematics and English Courses Taught in Interactive Learning Spaces at Ball State University

An Honors Thesis (HONR 499)

by

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Abstract

Research on modern learning spaces theorizes that space should support interactive learning and the social needs of the current and future student population. Interactive learning is defined as developing new ideas with peers and an expert on the subject matter through face-to-face discussion in groups. As students become increasingly more proficient with electronic devices, ILS also contributes to students' ability to present their own findings using technology available in the space. Therefore, since interactive learning is also expected to lead to higher student achievement, it would follow that ILS classrooms support higher student achievement as the space promotes interactive learning.

However, this data set of students enrolled in a lower-level math or an upper-level English course tells a different story. Two-sample t-tests for equal means were performed to compare averages of the change in pretest and posttest scores, weighted course grade, percentage of class sessions attended, and cumulative GPA between the ILS and traditional classrooms. It was found that the difference in means were insignificant for all the variables except cumulative GPA. A simple regression model was created to predict cumulative GPA, using weighted course grade and an indicator variable for ILS. It was found that the indicator variable for students who enrolled in a class taught in an ILS classroom was significant. But, contrary to the literature on modern learning spaces, this study found that ILS has a negative impact on student achievement. With modifications to the study, further research should be conducted to determine the impact of ILS on student achievement and learning.

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Purpose of Study

The purpose of this case study is to contribute to the comparative analysis of traditional classroom spaces versus Interactive Learning Spaces (ILS). The study focuses on two courses, a low-level math course and upper-level English course at Ball State University. More specifically, the study provides insight into ILS, classroom spaces geared toward interactive learning with the integration of technology such as smart boards, personal computers, and maneuverable furniture, as a contributing factor to student achievement. To answer this question, t-tests, correlations and multiple regression analysis were used to determine whether or not ILS was a contributing factor of student success during the fall semester of 2015.

Modern Learning Spaces in Higher Education

As technology becomes affordable and accessible, a connected culture of students attending higher education institutions rises. In response, an increasing number of institutions are beginning to address the needs of the current and upcoming students by integrating teaching methodologies that deviate from the traditional pedagogical approach by creating learning spaces to support interactive learning. Thus, the development of Interactive Learning Spaces (ILS), a potential replacement for the lecture oriented classroom, has become a point of experimentation, innovation, and research for institutions influenced by cognitive theory as well as the social characteristics of their student population.

Cognitive theory, presented in some educational literature, involves the study of active learning through collaboration. Active, constructive, and interactive learning are often used interchangeably to describe "active" learning, but Michelene Chi differentiates these terms with definitions and clear examples. Active learning is characterized as being physically engaged in an educational activity. Examples of active learning include paraphrasing, gesturing, or highlighting (Chi, 2009). Constructive learning is described as creating ideas within the self that extend beyond the initial information, for example, by constructing a concept map (Chi, 2009). While constructive learning transpires within an individual, interactive learning is a guided- or co-constructive process (Chi, 2009). For instance, interactive learning can be challenging an idea, arguing or defending a point, or responding to scaffoldings (Chi, 2009). From Chi's perspective, interactive learning is expected to lead to higher student achievement. Similarly, Malcolm Brown and Philip Long state the following:

> Learning literature agrees that learning can be enhanced, deepened, and made more meaningful if the curriculum makes the learners active participants through interactivity,

multiple roles (such as listener, critic, mentor, presenter), and social engagement (such as group work, discussion boards, wikis). (p. 2)

Interactive learning should take place in environments that stimulate the senses, encourage the interchange of information, and offer occasions for "rehearsal, feedback, application, and transfer" according to Nancy Chism (p. 4). The design of educational environments should facilitate social engagements discussed by both Chism and Brown and Long; hence, flexible, stimulating, and decentered environments could surpass traditional lecture classrooms in their ability to promote interactive learning (Chism, 2006; Brown & Long, 2006).

Characteristics of the student populations—digital, mobile, independent, social, and participatory—also contribute to physical space design (Lomas & Oblinger, 2006). Students today use devices such as mobile phones and laptops which often require classroom spaces to accommodate these items. The technology within the classroom can be used to enrich interactivity in the classroom such as student response systems, laptops combined with a wireless network, and podcasts that record discussion to be replayed (Lomas & Oblinger, 2006). Additionally, the technology utilized in educational spaces can provide educational support. For example, Lopez has found that interactive whiteboards help close achievement disparities for English language learners. While current students have integrated technology into their daily lives, the students of the entrepreneurial generation are self-driven, suggesting these students would prefer constructive learning; on the other hand, these upcoming students also prefer to interact with their friends face-to-face rather than via social media, signifying that interactive learning is a viable educational method (http://www.northeastern.edu/news/2014/11/innovation-imperative-meet-generation-z/). Likewise, many instructors find that interspersing interactivity, discussion, and group work in lecture engages learners (Lomas & Oblinger, 2006). Thus, the dialogue used in interactive learning forms communities of learners. Deborah Bickford and David Wright explain the importance of community in higher education: first, learning is a social process that thrives in a community setting, and, second, learning in community will have a critical role in preparing students for their professional work in the future. Even though learning spaces can enhance social interactions, these spaces also enable students to develop the communication skills applicable in all professions.

ILS could assist these initiatives of interactive learning as well as supporting the various social characteristics, both online and face-to-face, of the current and future entrepreneurial learner. In an interview with ILS faculty at Ball State University, ILS was defined as a classroom that encourages engagement through communication among the students and the expert present. Further, these spaces also feature technology and a nonlinear design with the intent of enhancing teaching and collaboration. Though components of ILS, such as the interactive whiteboards and interactive learning, may increase achievement; it is unclear whether or not the space as a whole can be a contributing factor to predicting academic achievement.

Course Descriptions and Teaching Methodologies

The two courses observed were English Linguistics (ENG 321) and Mathematics and Its Applications (MATH 125). Data were collected from 2 sections of ENG 321, one held in an ILS classroom and the other in a traditional classroom. For MATH 125, data were collected from 3 sections. Two sections were held in a traditional classroom, and the other section was taught in an ILS classroom.

The ENG 321 course focuses on the study of modern English grammar with special attention to phrase and sentence-level syntax. Moreover, the average cumulative hours earned for the students in the ENG 321 data set is 94 hours, indicating these students are mostly juniors and seniors. Thus, these students are studying and learning within an area of interest as an English major or minor. In addition, these students have experience with the demands of a college level course load.

As one considers the impact of space, the teaching methodology utilized the learning space. With a focus on student ideas, the teaching methodology in ENG 321 was the same in both sections observed. Students prepared for class by gaining a basic understanding of the content for the day by completing assignments such as reading a passage prior to attending class. Each class meeting began with a short assessment to ensure every student had prepared for class. The lesson then proceeded using the shared knowledge and working on the application of the concepts. The "flipped" classroom is often described as students learning the content outside of class followed by group work and discussion during class. Furthermore, the teaching methodology used in ENG 321 was described by the professor as "scrambled", as opposed to "flipped."

Moreover, the MATH 125 course can be generally described as a mathematics appreciation course with a diverse set of the topics, including statistics, finance, probability, voting theory, and graph theory. As opposed to the ENG 321 students, the average cumulative hours earned by students in the MATH 125 sections was 48 hours. This low value indicates these students are mostly freshmen and sophomores. Additionally, the majority of the students are taking the MATH 125 course as their mathematics core curriculum credit and the content of the course is most likely not in an area of interest for the students.

Comparable to ENG 321, the teaching methodologies used in MATH 125 implemented interactive principles. MATH 125 utilized a teaching methodology described as a modified "flipped" approach. "Mini-lectures" were delivered at the start of each class to offer clarification and to focus the class lesson before students worked in groups. In addition, the technology available in the traditional and ILS classrooms was utilized. However, the ILS classroom offered more opportunities to provide assistance to students, such as the ability to save class notes and electronically post them on Blackboard for students to review at their own leisure.

Interactive Learning Space Classrooms

The photos in Figures 1-3 provide snapshots of the classrooms where ENG 321 and MATH 125 were taught in the fall of 2015. The classroom in Figure 1 contains three projectors, one smart board, and seating for 36 students with access to personal whiteboards. Section 2 of ENG 321 was taught in this ILS room. The classroom in Figure 2 features two smart boards, one projector, individual whiteboards, and 24 node-style chairs. MATH 125, section 17, was taught in this ILS room. Figure 3 displays a typical traditional lecture style learning space that included one projector, stationary seating, and a large whiteboard or blackboard. The other three sections of ENG 321 and MATH 125 were taught in similar rooms.

Figure 1. ILS Classroom #1 (ENG 321)

Figure 2. ILS Classroom #2 (MATH 125)

Figure 3. Typical Traditional Classroom Space (ENG 321 & MATH 125)

Data Summary and t-Tests for Comparative Analysis

Participation in the study was voluntary. All sections for each course were taught by the same instructor. The explanatory variables collected included location, weighted course grade, percentage of class sessions attended, term hours attempted and earned during fall of 2015, cumulative GPA, undergraduate college entrance exam scores (SAT and ACT), cumulative hours attempted and earned, and projected GPA. Pretest and posttest assessments were collected in all sections of ENG 321 and MATH 125. The average percent difference between the pretest and posttest was used in the analysis because the maximum total points for the ENG 321 pretest and posttest was 5 while it was 10 for the MATH 125 tests. Table 1 below summarizes the location and enrollment numbers, as well as the pretest and posttest data for each section.

Course	Section	ILS	Number Enrolled	Number Completed Pretest and Posttest	Average Percent Difference between Pretest and Posttest
ENG 321	1	No	21	16	+11.94%
	2	Yes	14	9	+9%
MATH 125	15	No	35	24	+58.54%
	17	Yes	24	16	+56.88%
	112	No	32	31	+52.74%

Table 1. Summary Data for Pretest and Posttest by Section

The times in minutes for the pretest and posttest were also collected for the ENG 321 sections. However, since the times in minutes for the pretest and posttest were not collected for the MATH 125 sections, this information could not be utilized.

A noticeable observation in Table 1 is that the percent change in pretest and posttest scores for the MATH 125 sections are higher than the ENG 321 sections. This difference in averages is statistically significant when a two-sample t-test for equal means was performed as shown in Table 2. A possible reason for this difference in means is that the ENG 321 course refines students' grammatical skills as most of the students in the English data set have two to three years of college-level writing experience. On the other hand, the MATH 125 course is designed as a math appreciation course, so it is likely that the students in the MATH 125 data set have little predetermined understanding of the topics discussed in the course; therefore, the MATH 125 students have a greater potential for improvement as reflected in the average percent change in test scores.

Section Comparison Descriptions	Average Percent Difference in Pretest and Posttest	Estimated Difference μ_E - μ_M	95% CI for Difference	t-statistic	Degrees of Freedom	p-value
ENG 321 & MATH 125 Sections	$\mu_E = 0.1007$ $\mu_M = 0.556$	-0.4556	(-0.5100, -0.4012)	-16.65	88	0.000

Table 2. T-test for Average Percent Difference in Test Scores

The additional variables for each section, reported in Table 3, include the average cumulative GPA, average percent of classes attended, and average cumulative hours earned. Since this study examines student achievement, it is appropriate to consider the overall achievements of these students in aggregate and identify any inconsistencies in these academic achievement measures.

Course	Section	n	Average Cumulative GPA	Average Percent of Classes Attended	Average Cumulative Hours Earned
ENG 321	1	16	3.173	91.37%	100.75
	2	11	2.941	90.48%	84.55
MATH 125	15	33	3.004	93.33%	70.21
	17	21	2.904	91.75%	54
	112	32	3.281	95.21%	21.72

Table 3. Additional Variables by Section

For instance, when comparing sections 17 and 112 of MATH 125, the average cumulative GPA of section 17 is about 0.38 points below that of section 112. This indicates that the section 17 might not be able to achieve at the same academic level as section 112. Thus, it may not be advisable to use course grade to make a comparative analysis for the impact of ILS as the one section may have historically lower averages. After making this observation, 16 two-sample t-tests for equal means were performed to compare averages of the change in pretest and posttest scores, weighted course grade, percentage of class sessions attended, and cumulative GPA between course sections (one section in an ILS classroom and the other in a traditional classroom), as well as the ILS and traditional classrooms. Thus, a positive difference indicates a lower mean for the ILS classroom

Section Comparison Descriptions	Average Percent Difference in Pretest and Posttest	Estimated Difference in Means	95% CI for Difference	t-statistic	Degrees of Freedom	p-value
ENG 321 Sections 1 & 2	$\mu_1 = .1194$ $\mu_2 = .09$	0.0294	(-0.045, 0.104)	0.83	19	0.418
MATH 125 Sections 15 & 17	$\mu_{15} = .585$ $\mu_{17} = .569$	0.0167	(-0.095, 0.128)	0.30	37	0.764
MATH 125 Sections 17 & 112	$\mu_{112} = .527$ $\mu_{17} = .569$	-0.0413	(-0.139, 0.056)	-0.86	35	0.397
Traditional and ILS Classroom Sections	$\mu_T = .455$ $\mu_{ILS} = .367$	0.088	(-0.035,0.211)	1.45	43	0.155

Table 4. Average Percent Difference in Test Scores Comparison

The estimated differences in the average percent difference is pretest and posttest scores were found to be insignificant because the 95% CI for the differences all contain zero and the p-values are all greater than 0.10.

Section Comparison Descriptions	Weighted Course Grade	Estimated Difference in Means	95% CI for Difference	t-statistic	Degrees of Freedom	p-value
ENG 321 Sections 1 & 2	$\mu_1 = .8497$ $\mu_2 = .848$	0.0017	(-0.093, 0.097)	0.04	17	0.970
MATH 125 Sections 15 & 17	$\mu_{15} = .8388$ $\mu_{17} = .8725$	-0.0337	(-0.083, 0.016)	-1.38	44	0.176
MATH 125 Sections 112 & 17	$\mu_{112} = .872$ $\mu_{17} = .8725$	-0.0001	(-0.052, 0.052)	-0.00	47	0.997
Traditional and ILS Classroom Sections	$\mu_T = .8542$ $\mu_{ILS} = .864$	-0.0098	(-0.051,0.032)	-0.48	53	0.637

Table 5. Average Weighted Course Grade Comparison

Likewise, the estimated differences in the average weighted course grade were found to be insignificant because the 95% CI for the differences all contain zero and the p-values are all greater than 0.10. Another observation comparing the results in Table 4 and 5 is that the p-values for the estimated difference in the mean percent change in test scores are less than the p-values for the estimated difference in mean weighted course grades.

Section Comparison Descriptions	Percentage of Class Sessions Attended	Estimated Difference in Means	95% CI for Difference	t-statistic	Degrees of Freedom	p-value
ENG 321 Sections 1 & 2	$\mu_1 = .9137$ $\mu_2 = .9048$	0.0089	(-0.059, 0.077)	0.27	21	0.786
MATH 125 Sections 15 & 17	$\mu_{15} = .9333$ $\mu_{17} = .917$	0.0159	(-0.042, 0.074)	0.56	28	0.578
MATH 125 Sections 112 & 17	$\mu_{112} = .917$ $\mu_{17} = .9521$	0.0346	(- 0.024, 0.093)	1.21	30	0.237
Traditional and ILS Classroom Sections	$\mu_T = .9369$ $\mu_{ILS} = .913$	0.0238	(-0.017,0.065)	1.17	43	0.250

Table 6. Average Percentage of Class Sessions Attended Comparison

Again, the estimated differences in the percentage of class sessions attended were found to be insignificant because the 95% CI for the differences all contain zero and the p-values are all greater than 0.10.

Section Comparison Descriptions	Cumulative GPA	Estimated Difference in Means	95% CI for Difference	t-statistic	Degrees of Freedom	p-value
ENG 321 Sections 1 & 2	$\mu_1 = 3.173$ $\mu_2 = 2.941$	0.233	(-0.326, 0.792)	0.89	14	0.387
MATH 125 Sections 15 & 17	$\mu_{15} = 3.004$ $\mu_{17} = 3.904$	0.100	(-0.265, 0.464)	0.55	42	0.584
MATH 125 Sections 112 & 17	$\mu_{112} = 2.904$ $\mu_{17} = 3.281$	0.377	(0.038, 0.716)	2.26	35	0.03
Traditional and ILS Classroom Sections	$\mu_T = 3.147$ $\mu_{ILS} = 2.917$	0.230	(-0.044,0.504)	1.69	48	0.098

Table 7. Average Cumulative GPA Comparison

Furthermore, the estimated differences for the mean cumulative GPAs were found to be insignificant when comparing ENG 321 sections and MATH 125 sections 15 and 17 because the 95% CI for the differences all contain zero and the p-values are all greater than 0.10. On the other hand, the estimated difference when comparing MATH 125 sections 112 and 17 was significant at the 5% level. Therefore, one can be 95% confident that the difference between the mean cumulative GPA for the section 17, taught in an ILS classroom, and section 112, taught in a traditional classroom, is between the values 0.038 and 0.716. In other words, the average cumulative GPA for the MATH 125 section 17, taught in an ILS classroom, is less than the average cumulative GPA for a section 112, taught in a traditional classroom. When comparing the students in ILS and traditional classrooms, the estimated difference for the mean cumulative GPAs were found to be significant at the 10% level as shown by the p-value. Hence, using both the MATH 125 and ENG 321 data sets, a model could be created, to predict the cumulative GPA with ILS as a predictor.

Modeling

In order to build a multiple regression model to predict cumulative GPA, correlations were examined for the MATH 125 and ENG 321 data sets.

	Cumulative GPA	Percent of Class Sessions Attended	Percent Difference in Pretest and Posttest	Cumulative Hours Earned
Percent of Class Sessions Attended	0.413 0.000	-	-	-
Percent Difference in Pretest and Posttest	0.142 0.163	0.241 0.017	-	-
Cumulative Hours Earned	0.060 0.531	-0.148 0.118	-0.417 0.000	-
Weighted Course Grade	0.718 0.000	0.490 0.000	0.276 0.006	0.047 0.625

Table 8. Correlation Matrix for the Whole Data Set

Observing the correlations and p-values in Table 8, there is strong evidence that the correlations of percent class sessions attended and weighted course grade with cumulative GPA are significant. Thus, these variables were considered as explanatory variables when creating a model. In addition, subject was used as a categorical variable, and ILS was used as an indicator variable with 0 and 1 coded for the sections that were taught in a traditional and ILS classrooms. An initial model was run with all four variables to determine whether percent of class sessions attended or weighted course grade should be removed. Since a p-value of the correlation between these two variables is essentially zero, multicollinearity is present in the model, and, therefore, one variable should be removed. It was decided that the percent of class sessions attended should be removed because the variable was insignificant in the model (p-value of 0.509). In addition, subject was removed as a variable because it was also insignificant with a p-value of 0.316. Thus, weighted course grade (shown as Course_Grade in the MINITAB output) and ILS were determined to be significant predictors for modeling cumulative GPA, assuming cumulative GPA includes the fall 2015 semester.

Another step to building a model would be removing outliers with respect to their x and y values. Two observations were detected as outliers with respect to their x values. Additionally, there was strong evidence that four different observations were an outlier with respect to their y value. This process was repeated until all observations that had strong evidence of being an outlier with respect to its x or y value were removed; the criteria used to determine outliers were a leverage value greater than .035 or a standard residual greater in absolute value than 2.576. Seven observations were removed during the modeling process. After these outliers were removed, the F-value of the model increased which means the model became more significant, and the residual plots indicated a better linear fit of the data.

Looking at the output in Figure 4, one can examine the F-value of the model, p-values of the individual variables, and the R-squared and VIF values to determine the validity of the model. The F-value and p-value of the model indicate that the model is significant. The R-squared and R-squared (adj) indicate that the model explains 63% of the variability in the data. Given the sample size and nature of the data, this R-squared is acceptable. The variance inflation factors (VIF) do not raise concerns as they are about 1 which means that multicollinearity is not present in the model. In the final model, five observations were identified as possible outliers with respect to their y values. However, the standard residual in absolute value for each possible outlier was less than 2.576. So, these observations were left in the model.

Analysis of Variance

Source	DF	Adj SS	Adj MS	FValue	P-Value
Regression	2	18.5501	9.2750	89.00	0.000
Course_Grade	1	18.2913	18.2913	175.52	0.000
ILS	1	0.8702	0.8702	8.35	0.005
Error	103	10.7340	0.1042		
Total	105	29.2841			

Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
0.322821	63.35%	62.63%	61.12%

Coefficients

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	-0.934	0.313	-2.98	0.004	
Course_Grade	4.809	0.363	13.25	0.000	1.01
ILS					
1	-0.2065	0.0715	-2.89	0.005	1.01

Regression Equation

```
ILS
0     Cumulative_GPA = -0.934 + 4.809 Course_Grade

1     Cumulative_GPA = -1.141 + 4.809 Course_Grade
```

Fits and Diagnostics for Unusual Observations

Obs	Cumulative_GPA	Fit	Resid	Std Resid	
22	2.3690	3.0103	-0.6413	-2.02	R
43	1.8223	2.4565	-0.6342	-2.01	R
49	2.6496	3.3501	-0.7005	-2.19	R
53	2.2309	2.9095	-0.6786	-2.12	R
76	2.8666	3.5102	-0.6436	-2.01	R

R Large residual

Figure 4. Model for Predicting Cumulative GPA

To visualize the multiple regression model as shown in Figure 5, a scatterplot was used to display the linear relationship between weighted course grade and cumulative GPA. Figure 5 shows there is an upward linear trend in the data for both the ILS and traditional classroom students.

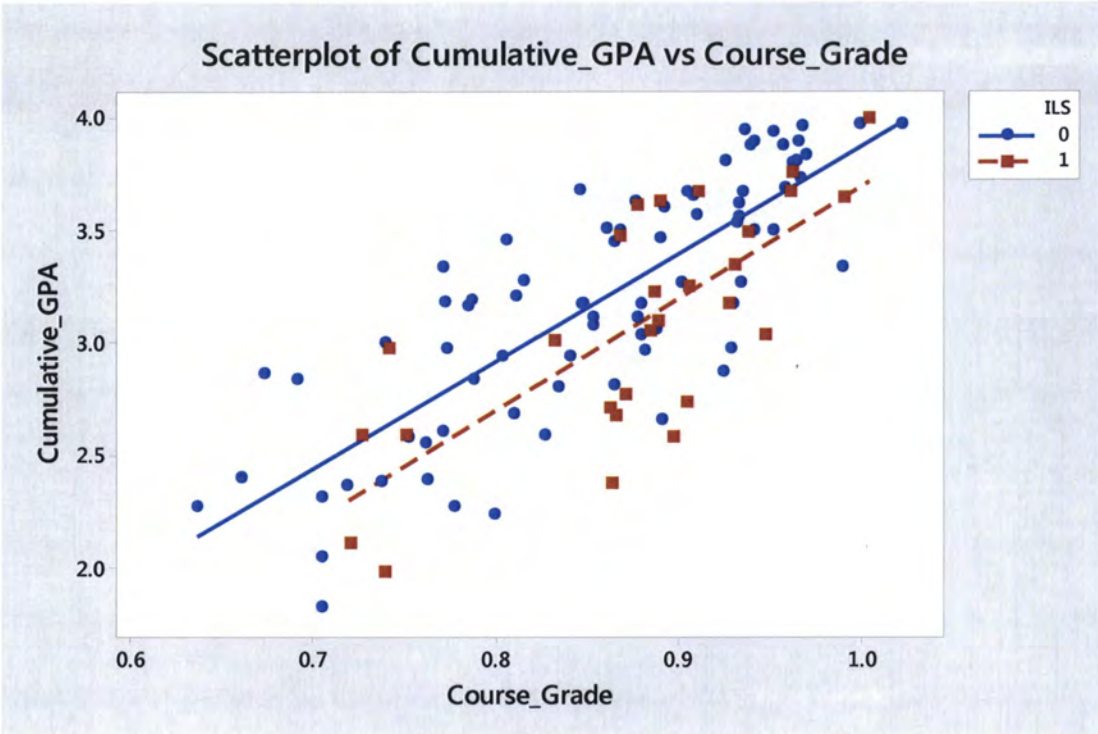

Figure 5. Model for Predicting Cumulative GPA

To further assess the model, a residual analysis was performed. Figure 6 contains four graphs: normal probability plot, residual versus fit plot, histogram of residuals versus frequency, and an observation order versus residual plot. From these graphs, one can determine if the linear regression assumptions are upheld. First, the residual versus fit plot indicates that the variance is reasonably constant across all fitted values and the assumption of correct functional form holds; a constant band across the graph, even number of points above and below the horizontal axis, and the lack of funneling and curvature in the residuals shows that these assumptions hold. The normality assumption is appropriate because the histogram in Figure 6 is reasonably bell-shaped and the residuals follow the straight line in the normal plot reasonably well. Lastly, the independence assumption holds because the observation order would not be relevant since the model was developed with cross-sectional data - observations collected at one point in time. Hence, all the regression assumptions hold for the model in Figure 4.

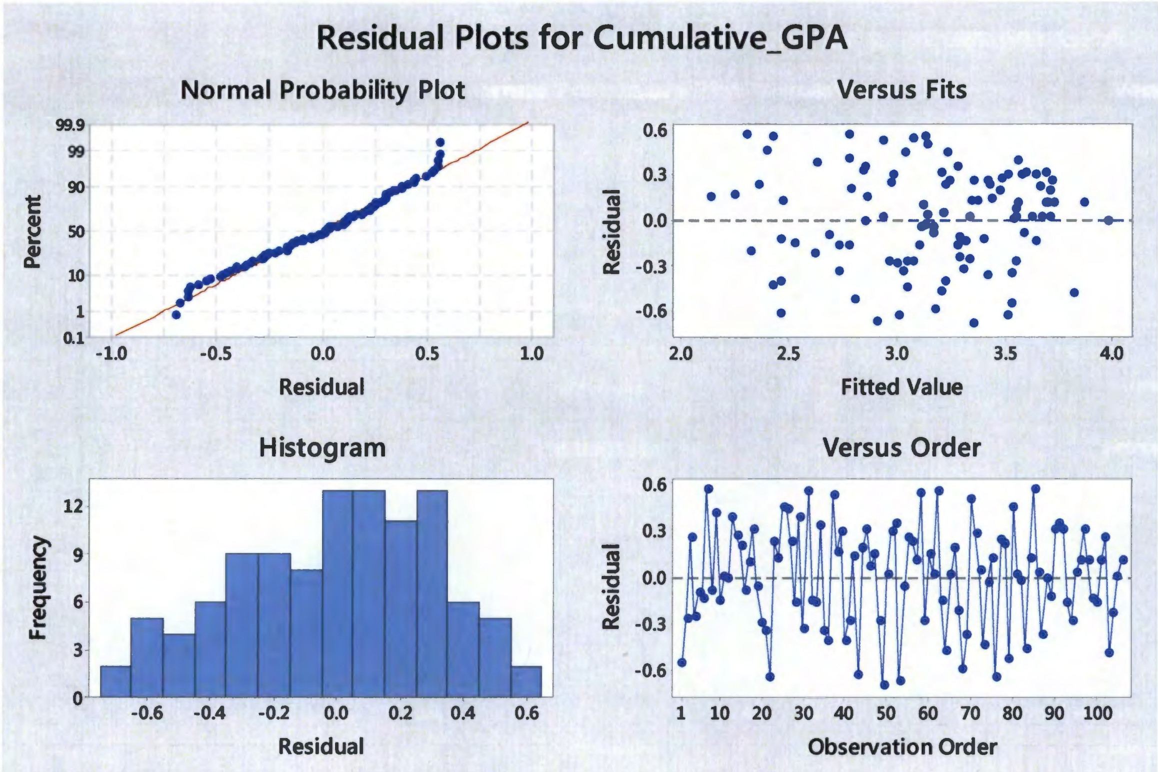

Figure 6. Residual Plots and Histogram

Since the model is valid for predicting cumulative GPA, it should be noted that ILS has a negative association with cumulative GPA as shown by the coefficient of -0.2065 in the regression output.

Conclusions and Discussion

Based on the literature that discusses modern learning spaces, the ILS classroom supports interactive learning which promotes student achievement. This study found there to be evidence that an ILS classroom did not have an impact on the average change in pretest and posttest scores, weighted course grade, and percent of class sessions attended when comparing data sets taught in an ILS and traditional classroom setting. However, if cumulative GPA is considered a measure of student achievement, then the data suggests that ILS negatively impacts student achievement.

Research about modern classroom spaces suggests that the nature of the material taught in ENG 321 may lend itself better to the ILS classroom. In ENG 321, students are often asked to create new knowledge from existing knowledge, and the space promotes this type of learning through the integration of technology and flexible furniture design. On the other hand, the objective of the MATH 125 course is to learn the established mathematical formulas and ideas; there is less focus on creating new ideas and more on mastering applications of mathematics. Therefore, it seems as though an ILS classroom would be a greater driver in student achievement for ENG 321. However, the comparison between the two subjects concluded that ENG 321 and MATH 125 did not differ in the effectiveness of ILS on student achievement.

These findings, that contradict the theory presented in the literature, may be due to limitations in the data set. The sample sizes were small, making it difficult to capture trends representative of the student population enrolled in courses taught in ILS classrooms. In addition, the small number of course subjects in the data did not appropriately represent the population of courses being taught in ILS classrooms. Therefore, a larger study should be performed with more course subjects represented in the data. The samples were also not random in that students were not randomly assigned to take a course in a particular classroom.

As learning spaces evolve, it is valuable for a university to understand the educational benefits and drawbacks of these spaces. Thus, further research should be conducted on the impact of ILS classrooms on student achievement. Suggestions for future studies include the following:

1. Collect random samples across more semesters to see if the impact of ILS classrooms changes as the Generation Z filters through the higher education system, and
2. Collect random samples across a large number of courses so that the university can understand the impact of the ILS classrooms.

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